Concrete Plant Operations Optimization Using Combined Simulation and Genetic Algorithms

Cao, Ming; Lu, Ming; Zhang, Jian-Ping

Published in:
Proceedings of the Third International Conference on Machine Learning and Cybernetics

Publication date:
2004

Proceedings of the Third International Conference on Machine Learning and Cybernetics, Shanghai, 26-29 August 2004

CONCRETE PLANT OPERATIONS OPTIMIZATION USING COMBINED SIMULATION AND GENETIC ALGORITHMS

MING CAO[1], MING LU[2], JIAN-PING ZHANG[3]

[1]PhD Student, Dept. of Civil Engineering, Tsinghua University, Beijing, China
[2]Assist. Professor, Dept. of Civil and Structural Engineering, Hong Kong Polytechnic University, Hong Kong, China
[3]Professor, Dept. of Civil Engineering, Tsinghua University, Beijing, China

Abstract:

This paper presents a new approach for concrete plant operations optimization by combining a ready mixed concrete (RMC) production simulation tool (called HKCONSIM) with a genetic algorithm (GA) based optimization procedure. A revamped HKCONSIM computer system can be used to automate the simulation model construction, conduct simulation experiments on certain scenarios of site orders and resource provisions, and optimize the system performance measures under a stochastic simulation environment. HKCONSIM is suitable for assisting a RMC plant in its resource provision planning and concrete production scheduling in order to meet given demands at a number of sites for concrete over a working day, determine the least costly, most productive amount of truckmixer resources to improve the supply service level and the utilization level of the truckmixer resources available. To simulate and optimize the RMC production operations with HKCONSIM does not require familiarity by the user with any software-specific terminology and modeling schematics; simulation model construction can be easily achieved by specifying the attributes for each pour and site and providing the plant and truck-mixer resources available on self-explanatory on-screen forms. This paper also presents two case studies for optimizing concrete plant daily operations based on Hong Kong's real operations data. Conclusions are given on the research and recommendations for future work made.

Keywords:

Genetic Algorithm; Stochastic Optimization; Discrete-Event Simulation; Ready Mixed Concrete

1. Introduction

Ready mixed concrete (RMC) accounts for an increasingly high proportion of the concrete consumed on residential building, heavy and highway construction projects. Compared with on-site mixed concrete, RMC affords the advantages of stable quality, less pollution and less working space requirement, which are of significance to many construction sites, especially those in crowded large cities such as Hong Kong, Beijing and Tianjin. In these cities, many central concrete plants are in operation and more are being established in order to meet the growing demand of concrete in construction sites. A study benchmarking the performance of concrete placing in buildings (covering Hong Kong, Beijing, UK, and Germany) has found that metropolitan areas typically adopt the one-plant-multi-site RMC production and supply system; site productivity is influenced not only by the placing method and other site factors but also by an inevitable imperfect concrete supply [1]. Timely concrete delivery by truckmixers on site contributes to not only continuous, productive site operations on the side of contractors, but also the cost-effective utilization of limited truckmixer resources on the side of the plant. Hence, enhancing the coordination between a RMC plant and the sites is as critical to improving the productivity of the placing operation, as enhancing the efficiency with which sites and the RMC plant are separately managed. In order to become profitable and competitive, it is also crucial for a RMC business to be able to deploy less truckmixer resources and marshal more efficiently its truck-mixer fleet in running its daily operations.

The present research is mainly concerned with how to apply operations simulation modeling and GA optimization to resource planning and production planning of a RMC plant in order to achieve better plant-site coordination and meet the daily demand of sites for concrete. The emphasis of the simulation and optimization model is on (1) the estimation of the number of truckmxiers of certain volume capacity to be deployed, (2) the estimation of the interarrival times of consecutive truckmixers on different sites (i.e. the supply rate), (3) the service levels in terms of timely delivery achieved on each site, and (4) the utilization levels of plant resources available (i.e. mainly the batching bays and truckmixers).

2. Review of Previous Related Work

2.1. Operations simulation

Simulation is to imitate the operations of a real-world process or system over time [2]. Operations simulation has been proven as an effective tool for engineering complex construction processes that feature dynamic queuing and resource interactions. The best known construction simulation method is the activity cycle diagram based CYCLONE, which uses six modeling elements to model typical, repetitive construction processes [3]. The development of the activity-based construction simulation method (ABC) is intended for making simulation as easy as the critical path method (CPM) without compromising the functionality of simulation [4]. The simplified discrete-event simulation approach (SDESA) further streamlined the algorithm and modeling schematics for discrete-event simulation [5]. The executive program of SDESA controls the simulation operations by manipulating two dynamic queues, namely, the flow entity queue and the resource entity queue. A flow entity, passing through a sequence of activities in a process, is an essential element with common time attributes to initialize an activity, engage with resource entities, and acts as a key to control the execution of an activity. SDESA distinguishes disposable resource entities from reusable ones to represent some intermediate products or command units that can be used once only. SDESA was particularly adopted for creating the simulation tool of HKCONSIM [6] after twenty weeks during 1999/2000 period were spent in observing the practical RMC operations in Hong Kong and collecting fifteen operational days of reliable and substantially complete data [7]. HKCONSIM drew on these raw data in establishing statistical distributions for activity durations such as loading concrete, plant-site travel time, unloading concrete etc.

2.2. Genetic algorithms

The GA was conceptualized by John Holland in the 1970s, and was originally devised as an algorithm for optimization search and for computationally studying the process of evolution [8]. The basic idea is that by following the rule of "the survival of the fittest", many different possible solutions (i.e. the chromosomes) to a problem compete amongst themselves, replicate, mate (or crossover), mutate, are evaluated with respect to an objective function, and further evolve according to the evaluation result (i.e., the higher the fitness score for a chromosome, the more chance for the chromosome to survive and further evolve). GA has been used successfully to tackle numerous resource scheduling applications, including the resource allocation and leveling combined scheduling [9], the optimization of resource-activity critical-path method [10] and the resource optimization in operations simulation [11].

3. HKCONSIM System

3.1. Concrete production/delivery operations modeling

HKCONSIM allows the user to input the site demand attributes through a simple site demand assignment form (Figure 1). These attributes include the site ID, the volume of concrete ordered (in cubic meters), the plant-to-site traveling distance range, the method for placing concrete, the site requirement for truckmixer volume capacity (i.e. 5 m^3 only, or 7 m^3 only, or no specific requirement), the first truckmixer's arrival time (i.e. when site crews and equipment are ready to start pouring operations), the estimated inter-arrival time of consecutive truckmixers (i.e. the average time of unloading a truckmixer relating to the site placing method), and the priority of a site (e.g. the plant operator may assign a higher priority to a pour with a larger volume of concrete ordered; when multiple sites request concrete simultaneously, the next returning truckmixer is dispatched to the site with the highest priority).

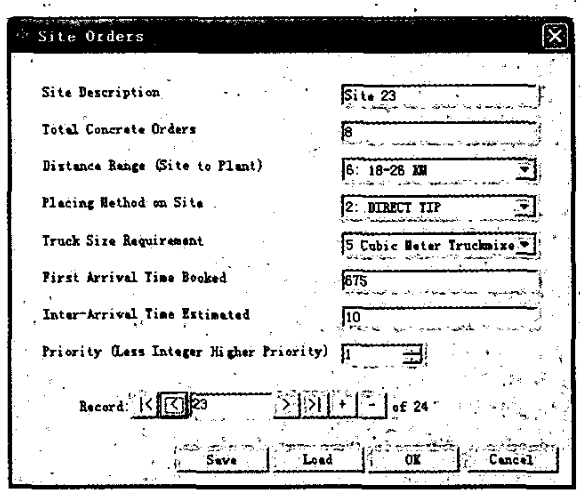

Figure 1. Site Demand Assignment

Based on the site demand data entered, HKCONSIM can automatically generate the SDESA simulation model. Since the concrete plant usually serves a large number of sites in its daily operations, the one-site-multi-site simulation model is created for dealing with each site individually and explicitly. Figure 2 shows the one-plant-multi-site SDESA model. The RMC production and delivery process is divided into 6 distinct activities, i.e. batching and loading concrete into the truckmixer; washing and checking out the truckmixer at the plant; the truckmixer traveling to a specified site; unloading the truckmixer on site using a particular placing method; washing out plus waiting on site; and the truckmixer returning to the plant). Statistical distributions for these activities' duration are classified by the size of truckmixers, the plant to site distance range, the placing method on site. In order to control the interval of dispatching consecutive truckmixers to a certain site, another activity called "Interval" is added into the model. This activity requires no resources and its duration is set as the inter-arrival time of consecutive truckmixers estimated for the specified site. This "interval" activity will be activated following the completion of batching and loading one truckmixer. When the "interval" activity finishes, another request for truckmixer (a flow entity) will be inserted to the waiting list for the "batch & load" activity to process. In dealing with those sites that accept both the 5 m^3 and 7 m^3 truckmixers, the concept of "Substitute Resource" is introduced into this model, which allows the user to assign different types of resources that can be alternatively used by an activity subject to availability and user-defined priorities. A similar process model is generated for each site that the plant serves, enabling the simulation tool to handle each site individually and track site service performance.

3.2. SDESA operations simulation

After the simulation model is set up, the user can take advantage of the tools and functions provided by the SDESA simulation environment to simulate and analyze the concrete plant operations. The SDESA executive selects an unprocessed flow entity (i.e. the site order) with the earliest arrival time from the flow entity queue for processing, which can be regarded as observing the first-in-first-out queue discipline. The simulation process ends when (1) there is no any entity in the flow entity queue or (2) all the flow entities in the queue can not be processed because not enough resources are available in the resource pool (i.e. resources become unavailable as the total simulation time is over) or certain control conditions are satisfied (e.g. concrete as ordered have all been delivered).

Through the simulation, the user can easily find the complicated relationships between the patterns of demand for concrete, the plant and truckmixer resources available to the system, and both the service levels achieved on sites and the utilization levels achieved for the resources involved [6]. Note that the original HKCONSIM is merely a simulation tool, which is capable of analyzing the performance of the plant operations given certain amounts of truckmixers of different volume capacity and interarrival times on sites. A trial-and-error approach is required to experiment with various combinations of resource provisions and site interarrival times in attempts to improve the site service levels and the resource utilization rates. However, given the large number of possible resource and time combinations, trial and error is too time-consuming to arrive at a solution, and does not guarantee an optimal solution to such a complex NP-complete problem under uncertain constraints.

3.3. GA formulation

GA is applied for optimization of an HKCONSIM operations simulation model with the optimization variables set as the amounts of truckmixers and the truck inter-arrival times. The first two positions in the chromosome string are the amounts of the 5 m^3 and 7 m^3 truckmixers (Hong Kong's common practice), respectively, and the following positions are the interarrival times set for each site (Fig. 3).

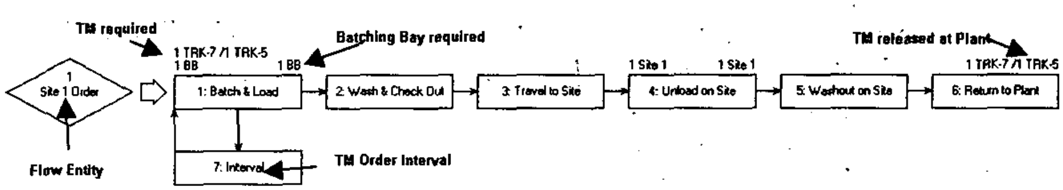

Figure 2. One-Plant-Multi-Site model

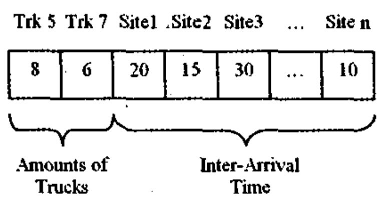

Figure 3. Gene Structure for the GA Optimization

HKCONSIM provides two different optimization objectives for the users to choose from (Figure 4). The first objective is to minimize the site idle time and improve the site service level (SSL) achieved by the RMC plant; the objective function takes the form of adding up the site idle time incurred on all the sites during the simulated period. The other objective is to minimize the idle times concerning all plant and site resources in the system, including the batching bay, the truckmixers and the site crews; the objective function is then defined as the total operational inefficiency time (TOI). Note that the performance measures of SSL and TOI were proposed and clearly defined by Lu [12].

The steady-state GA is applied to optimize the HKCONSIM. The system first generates an initial "population" of random chromosomes, and then evaluates the fitness score for each chromosome in terms of its average SSL or TOI values obtained from multiple simulation runs (say 30), attempting to reduce the influence of randomness on simulation outputs due to Monte Carlo sampling processes in simulation. Next, two chromosomes with higher fitness scores are selected from the population to reproduce offspring chromosomes as follows: a random num p between 0 and 1 is generated; if p is less than the crossover probability (Pco) then uniform crossover the pair, otherwise change each bit of the pair by the mutation rate (Pmu). Either crossover or mutation operations will result in two new chromosomes added to the population. The population is then ranked by the fitness scores of chromosomes, and the two achieving the lowest fitness scores are removed from the population. The stopping criteria for the optimization are as: (1) no improvement has been observed on the objective function over two consecutive iteration intervals or (2) a maximum of iterations (e.g., 10000) is reached.

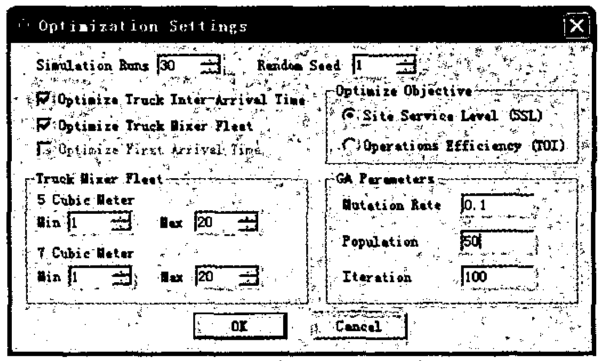

Figure 4. Optimization Settings

4. Case Study

This section presents two case studies for applying the simulation-GA combined approach and the revamped HKCONSIM computer system to optimize concrete plant daily operations based on Hong Kong's real operations data.

4.1. Twenty-four sites case

The first case study looks into a Hong Kong concrete plant on a particular day, serving 24 sites to supply a total of 386 m^3 of concrete in its daily operations. The distance between these sites and the plant ranges from 4 kilometers to more than 30 kilometers.

The optimization objective is set as improving the site service level (SSL), i.e. to minimize the total site idle time due to tardy concrete delivery. The truck interarrival times and the number of trucks are all set as optimization variables. The number of simulation runs for evaluating the fitness score (SSL) by GA is set as 30 and the iteration interval for checking GA's progress is set at every 100 iterations.

The optimization procedure took about 3 hours on a Pentium IV 2.0 GHz PC to complete. Table 1 shows the site demand settings and the optimization results. Note that the truckmixers engaged increase from the original 14 (i.e. 8 5m^3 truck and 6 7m^3 truck) to optimized 29 (9 5m^3 and 20 7m^3 respectively), the inter-arrival times are also shortened for all sites. Meanwhile, the total site idle time (SSL) in terms of 30 runs average decreases from 1429.47 min to 97.57 min, but the averaged total operation inefficiency time increases from 4326.05 min to 8498.73 min as the expense of improving site service levels by adding 15 extra truckmixers.

Table 1. Site Demand and Optimization Result of the 24 Sites Example

Site ID	Total Quantity	Distance	Placing Method	Spec. Truck	First Arrival	Origin Interval	Optimal Interval
1	80	6~10 km	2 SKIPS	Both	30	30	17
2	2	30~34 km	1 SKIP	Both	75	N/A	N/A
3	1	30~34 km	1 SKIP	Both	375	N/A	N/A
4	2	30~34 km	1 SKIP	Both	390	N/A	N/A
5	16	6~10 km	2 SKIPS	Both	60	60	10
6	5	30~34 km	2 SKIPS	5 m^3	105	N/A	N/A
7	3	30~34 km	1 SKIP	Both	435	N/A	N/A
8	7	30~34 km	2 SKIPS	7 m^3	450	60	10
9	7	6~10 km	HOIST & BARROW	Both	75	60	14
10	52	6~10 km	PUMP	Both	75	30	8
11	8	4~5 km	HOIST & BARROW	Both	100	90	5
12	45	6~10 km	2 SKIPS	Both	120	45	20
13	58	6~10 km	PUMP	Both	135	40	10
14	14	30~34 km	2 SKIPS	Both	225	40	19
15	24	6~10 km	2 SKIPS	Both	345	20	6
16	3	18~26 km	HOIST & BARROW	Both	390	N/A	N/A
17	21	6~10 km	PUMP	7 m^3	405	45	5
18	1	6~10 km	DIRECT TIP	Both	420	N/A	N/A
19	1	6~10 km	DIRECT TIP	Both	495	N/A	N/A
20	4	6~10 km	DIRECT TIP	Both	435	N/A	N/A
21	8	30~34 km	DIRECT TIP	Both	465	120	9
22	6	6~10 km	DIRECT TIP	7 m^3	450	N/A	N/A
23	8	18~26 km	DIRECT TIP	5 m^3	675	10	8
24	10	4~5 km	DIRECT TIP	Both	690	60	6
					5 m^3	8	9
					7 m^3	6	20
					Opt-Time	N/A	3 hr
					TOI	4326.05	8498.73
					SSL	1429.47	97.57

4.2. Thirty-one sites case

The second case study is also based on one-day real site demand data obtained from Hong Kong. In this example the optimization objective is set as improving the total operation efficiency, i.e. to minimize the total operations inefficiency (TOI) time. The optimization settings are the same as the previous example.

The optimization procedure took about 3 hours 48 minutes on the same computer. Table 2 shows the site demand settings and the optimization results. Note that the numbers of truckmixers engaged decrease from 20 to 12 (from 10-5m^3 trucks and 10-7m^3 trucks to 2-5m^3 trucks and 10-7m^3 trucks), the inter-arrival times have increased or decreased on different sites. The total time of operations inefficiency is greatly shortened from the original 6244.62 min to the optimized 2778.55 min. But the site idle time (SSL), by contrast, increases from 497.60 min to 1271.14 min due to shrinking the truckmixer fleet size.

Table 2. Site Demand and Optimization Result of the 31 Sites Example

Site ID	Total Quantity	Distance	Placing Method	Spec. Trk	First Arrival	Origin Interval	Opt. Interval
1	16.5	3 km	2 SKIPS	Both	60	20	20
2	10	4~5 km	2 SKIPS	Both	90	20	5
3	15	18~26km	2 SKIPS	Both	105	20	20
4	61.2	3 km	PUMP	Both	105	15	20
5	3	18~26km	HOIST & BARROW	Both	150	N/A	N/A
6	3	4 - 5 km	2 SKIPS	Both	135	N/A	N/A
7	35.5	6~10km	PUMP	Both	150	15	20
8	19.3	4~5 km	2 SKIPS	Both	150	20	52
9	5	4~5 km	DIRECT TIP	Both	210	N/A	N/A
10	7.1	4~5 km	2 SKIPS	Both	255	20	47
11	128.2	4~5 km	PUMP	Both	60	25	20
12	8.1	4~5 km	1 SKIP	Both	450	20	14
13	10	4~5 km	2 SKIPS	Both	555	20	30
14	20	6~10km	PUMP	Both	465	15	13
15	20.7	6~10km	2 SKIPS	Both	510	20	31
16	32.3	6~10km	1 SKIP	Both	405	20	20
17	5	6~10km	DIRECT TIP	Both	525	N/A	N/A
18	5	6~10km	DIRECT TIP	Both	555	N/A	N/A
19	6	4~5 km	DIRECT TIP	Both	15	10	20
20	24.2	4~5 km	1 SKIP	Both	15	20	9
21	11.6	4~5 km	2 SKIPS	Both	120	20	20
22	7	4~5 km	2 SKIPS	Both	30	20	20
23	12.6	4~5 km	2 SKIPS	Both	135	20	20
24	4	6~10km	BACKHOE	Both	180	N/A	N/A
25	4	18~26km	BACKHOE	Both	450	N/A	N/A
26	5.1	4~5 km	2 SKIPS	Both	420	20	20
27	5	4~5 km	DIRECT TIP	Both	525	N/A	N/A
28	14.2	6~10km	2 SKIPS	Both	555	20	20
29	7.1	4~5 km	2 SKIPS	Both	585	20	20
30	5.1	3 km	2 SKIPS	Both	585	20	20
31	11	6~10km	2 SKIPS	Both	615	20	20
					5 m^3	10	2
					7 m^3	10	10
					Opt-Time	N/A	3.8 hr
					TOI	6244.62	2778.55
					SSL	497.60	1271.14

4.3. Comparison of two optimization objectives

Table 3 compares the resource utilization rates in terms of working percentage for the above two case studies. It is seen that when the site service level (SSL) is selected as the optimization objective (as in the 24 sites example), the sites resources' utilization rate are higher than in the original case, but the truckmixer resources are relatively underutilized (averaging 45%) . This optimization mode is most suited to situations in which the concrete plant has sufficient truckmixers and intends to improve their service level by providing adequate plant resources.

By contrast, when the total operations efficiency (TOI) is selected as the optimization objective (as in the 31 sites example), the site idle time is longer, but the utilization rate of truckmixers is much higher (nearly 90%). Hence, this mode caters to scenarios (1) when the concrete plants do not have enough truckmixers and hope to improve their truckmixers' utilization rates, or (2) when improvements on the efficiency of the whole system's performance are desired.

Table 3. Resource Utilization Rate in Two Scenarios

Resource	24 Sites Example		31 Sites Example	
	Origin	Optimized	Origin	Optimized
Batching Bay	22.34%	25.39%	35.64%	37.02%
5 m^3 Truckmixer	74.96%	47.45%	60.51%	90.04%
7 m^3 Truckmixer	71.64%	42.70%	57.09%	86.17%
Sites	53.79%	94.61%	82.57%	65.16%

5. Conclusions

Combined simulation and genetic algorithms can be successfully applied to model and optimize the concrete plant operations in a practical one-plant-multi-site concrete production and supply setting. The genetic optimization is suitable for finding the near-optimal solutions in a relatively short time. The two different optimization objectives (i.e. SSL and TOI) can be used in different situations to address different priorities. Taking the SSL objective can reduce the site idle time, improving the site service level. By contrast, selecting the TOI objective can increase the plant's resource utilization rates and the overall efficiency of the total system. The simulation-optimization tool developed will help the users to analyze the performance of a complicated logistics system and evaluate various scenarios postulated.

In the ongoing research, the HKCONSIM is being tested on real projects to improve plant daily operations planning and truckmixer deployment and dispatching, and will be further augmented to (1) model the multi-plant-multi-site model that allows the construction sites to have more than one concrete producers, (2) allow multiple objective optimizations (e.g. the total operation time, the cost of the plant and the sites, etc.), and (3) consider the quality standards achieved (e.g. the freshness of delivered concrete) and (4) the relative importance of each site customer as appreciated by the plant operator (e.g. pour size, client loyalty are such factors).

Acknowledgements

The research presented in this paper has been substantially supported by Hong Kong Research Grants Council (Project A/C B-Q580 PolyU5049/02E), and partly funded by the Hong Kong Polytechnic Univ. - Tsinghua Univ. Research Center for Construction IT.

References

[1] Anson, M., Wang, S. Q. and Wang, Y. S. (1996) "The concreting of Hong Kong buildings." Dept. of Civil and Structural Engineering, Construction Industry Development Studies and Research Center, Hong Kong Polytechnic Univ., Hung Hom, Hong Kong.

[2] Banks, J., John, S. C., Nelson, B. L. and Nicol, D. M. (2000), Discrete-Event System Simulation 3rd Edition, Prentice Hall, NJ.

[3] Halpin, D. W. and Riggs, L. (1992), "Planning and analysis of construction operations", Wiley, New York.

[4] Shi, J. (1999) "Activity-Based Construction (ABC) Modeling and Simulation Method", ASCE Journal of Construction Engineering and Management, 125(5), 354-360

[5] Lu, M. (2003), "Simplified Discrete-Event Simulation Approach for Construction Simulation", ASCE Journal of Construction Engineering and Management, 129 (5), 537-546

[6] Lu, M., Anson, M., Tang, S. L. and Ying, Y. C. (2003) "HKCONSIM: A Practical Simulation Solution to Planning Concrete Plant Operations in Hong Kong", ASCE Journal of Construction Engineering and Management, 129 (5), 547-554

[7] Anson, M., Tang, S. L., Ying, K. C. (2002) "Measurement of the performance of ready mixed concreting resources as data for system simulation", Construction Management and Economics, Vol. 20, 237-250

[8] Holland, J.H. (1975) "Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence" University of Michigan Press, Ann Arbor, MI.

[9] Chan, W., Chua, D. and Kannan, G. (1996) "Construction Resource Scheduling with Genetic Algorithms", ASCE Journal of Construction Engineering and Management, 112(2), 125-132

[10] Wang, P., and Lu, M. (2002). "Genetic algorithm optimized resource activity critical path method", Proceedings of the first international conference on machine learning and cybernetics, pp: 1978-1982, IEEE & HBU, Beijing, China, Nov. 2002

[11] Hegazy, T. and Kassab M. (2003) "Resource Optimization Using Combined Simulation and Genetic Algorithms", ASCE Journal of Construction Engineering and Management, 129 (6), 698-705

[12] Lu, M. (2002), "HKCONSIM: a simulation platform for planning and optimizing concrete plant operations in Hong Kong", Proceedings of International conference on innovation and sustainable development of civil engineering in the 21st century, 278-283, Aug. 2002, HKIE & CCES, Beijing, China.